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Cooperative transmission in delay tolerant network

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Abstract: The delay tolerant network (DTN) is an emerging concept, which is used to describe the network, where the communication link may disrupt frequently. To cope with this problem, the DTN uses the store-carry-forward (SCF) transmission mode. With this policy, the messages in the DTN are transmitted based on the nodes' cooperation. However, the nodes may be selfish, so the source has to pay certain rewards for others to get their help. This paper studies the optimal incentive policy to maximize the source's final utility. First, it models the message spreading process as several ordinary differential equations (ODEs) based on the mean-field approximation. Then, it mathematically gets the optimal policy and explores the structure of the policy. Finally, it checks the accuracy of the ODEs model and shows the advantages of the optimal policy through simulation and theoretical results respectively.

Keywords: delay tolerant network (DTN), optimal control, message transmission.

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1. Introduction

With the rapid development of the smart terminals (e.g., smart phones, vehicles, laptops, etc.), the mobile data traffic faces an explosive growth [1]. According to the forecast in [2], in 2021, the global mobile data traffic is expected to reach about 49 exabytes per month at a compound annual growth rate of 47%. Such growth causes unprecedented pressure on the cellular networks and pushes them to deploy more infrastructures to increase the communication capacity. Correspondingly, this will bring much more expenditure. Therefore, the network operators may need a low-cost method to offload the mobile data traffic burden. In this case, many works try to use the WiFi embedded in the smart terminals to offload the traffic [3,4]. Due to the limited coverage of WiFi and the mobility of the smart terminal owners, the communication link is dynamic and uncertain. Such network is often called the delay tolerant network (DTN) [5].

To cope with the disruption of the link, the DTN often adopts the store-carry-forward (SCF) communication mode. Generally speaking, in this mode, when receiving a message, the node will first store it in its buffer and carry the message with its movement. Then, if the node encounters with a node without the message, it will forward the message. Obviously, the SCF mode needs the cooperation between the nodes. However, in the real applications, the device owners may be selfish and may not be willing to help others. As shown in [6], people may just be altruistic for their friends. Therefore, if the source (node that generates a message) wants to get help from others, it has to use some incentive policies. In [6], Li et al. presented a user-centered incentive policy which can adapt selfishness. Then, Lu et al. [7] presented a practical incentive policy, which attached some rewards on each message. In this case, if a node forwards a message to the destination, the node will get rewards. Seregina et al. introduced another reward-based incentive policy, where only the first node to deliver a message to the destination can get the given rewards [8]. However, it only considered the two-hop routing policy, so the relay nodes cannot forward the message to others besides the destination. Cai et al. [9] also presented an incentive policy for the two-hop routing protocol. It first ensured the nodes' honesty by employing the famous Vickrey-Clarke-Groves (VCG) auction, and then an optimal relay selection method based on the optimal sequential stopping rule was proposed. Similar to our work, Nguyen et al. introduced an incentive policy, which was obtained through solving an optimization problem based on the mean-field approximation, but still it only considered the two-hop routing protocol [10]. In addition, the source only pays rewards for the first nodes successfully delivering the message to the destination like [8]. In addition, it supposes that the rewards are fixed as a premise. Chen et al. [11] proposed a game theoretical incentive policy, which assigned credits for message forwarding and storage in proportional to the priorities in the routing poli-

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cy. Jedar et al. [12] presented another game based incentive policy, and it mainly considered the factor that selfishness may depend on the social relation between the nodes. That is, the selfish degree may be different between different links. There are also many other works that have explored the incentive policies in the DTN, and this paper does not introduce them one by one here.

As shown above, many works have explored the incentive policy in the DTN from different angles. Some of them use game theory with the assumption that nodes are rational and compete with each other to maximize their own incomes. Others suppose the nodes will passively receive the rewards the source pays and do not compete with each other. These policies adapt to different scenarios. However, the common core of these works is that the performance improvement depends on the rewards paid by the source. Generally speaking, the level of the nodes' cooperation is in proportional to the quantity of the rewards. In other words, if the source wants to get much more help from a node, it may need to pay more rewards. In the real application, the source cannot afford too much cost, so it may want to get a proper trade-off between the routing performance and its cost, which is the main objective of this paper. At present, fewer works consider this problem. Different from most of the above works, this paper studies the incentive policy with the epidemic routing protocol, where a node can transmit the message to every nodes. On the other hand, most of the related works have checked the performance of their incentive policies through simulation, so it is hard to show whether these policies are optimal in a given scenario. For this reason, this paper will mathematically explore the incentive problem to get the best trade-off between the source's cost and the final performance. In addition, it supposes that the nodes do not compete with each other similar to the above works without game theory. The main contributions of this paper can be summarized as follows:

(i) It defines the relation between the incentive policy and the forwarding policy, and theoretically models the message spreading process according to the mean-field approximation.

(ii) Based on the theoretical model, it describes the incentive problem as an optimal control problem. Then, it obtains the optimal policy based on Pontryagin's maximum principle, and proves that the optimal policy has a bang-bang structure.

(iii) Finally, it checks the accuracy of the theoretical model through simulations with both synthetic and real motion traces. In addition, it also shows the advantages of the optimal policy through numerical results.

Remarks: due to the sparse communication opportunities, the references between the links in the DTN are often ignored.

2. Message transmission modeling

2.1 Basic settings

Suppose there are N nodes, which include one source. $N-1$ nodes are often called the relay nodes, which will help to forward a message to the destination for the source. In addition, there is another node denoted as destination. At the initial stage, the source generates a message and wants to forward it to the destination before the deadline T. However, due to selfishness, these relay nodes may not be altruistic and they forward the message with a probability $q < 1$. Generally speaking, the value of q may be varying with time. Since the objective of this paper is to consider the optimal incentive policy, for simplicity this paper sets q as a constant, but the work can be extended to the case without the assumption easily.

In the SCF communication mode, message exchange happens only when the nodes contact each other, so it closely depends on the mobility model. At present, many works have shown that the humans' and vehicles' moving rule can be described as the exponential model [13,14]. Therefore, many theoretical works in the DTN adopt the model [15,16]. In the exponential model, the inter-meeting time between two consecutive contacts conforms to the exponential distribution. For example, in the time interval Δt, two nodes meet with each other with the probability $1-\exp(-\lambda\Delta t)$, and the parameter λ can be called the meeting rate.

To make the relay nodes cooperative, the source will pay some rewards which vary with time. This paper supposes that the rewards are in proportional with the cooperative probability. In particular, at time t, cooperative probability is denoted as $u(t)$, and the rewards the source has to pay is $\varepsilon u(t)$. ε is a positive constant, which is used to denote the cost for getting the nodes' help.

2.2 Message transmission analysis

As shown above, if there is no incentive, two nodes exchange a message with the probability q once they encounter each other. Therefore, under the incentive policy, at time t, the probability that the message can be transmitted can be denoted as $1-(1-q)(1-\varepsilon u(t))$. Let $i(t)$ denote the ratio of nodes carrying the message at time t. That is, if there are $I(t)$ replicas in the network, $i(t)$ satisfies $i(t) = I(t)/N$. Then

$$I(t+\Delta t) = I(t) + \sum_{j=1}^{N-I(t)} (1-\mathrm{e}^{-\beta I(t)\Delta t})\cdot$$
$$(1-(1-q)(1-\varepsilon u(t))). \qquad (1)$$

Because only the source has the message at the initial stage, it can be got $I(t) = 1$ and $i(t) = 1/N$. Then, according to the mean-filed theory [17], we can obtain

$$\dot{i}(t) = \beta N i(t)(1 - i(t))(1 - (1 - q)(1 - u(t))). \quad (2)$$

In fact, (2) is obtained from the mean-filed theory, which is an approximation, so it needs to check the accuracy.

Similarly, let $F(t)$ denote the probability that the destination gets the message at time t:

$$\dot{F}(t) = \beta N i(t)(1 - F(t)). \quad (3)$$

$F(t)$ is often called the delivery ratio, and it is a main metric to describe the performance in the DTN. For simplicity, suppose that the nodes are willing to forward the message to the destination with the probability of 1. In fact, this assumption also can be released and has no impact on the analysis. Then, the objective of this paper is to solve the following function:

$$\max U(T) = F(T) - \varepsilon \int_0^T u(t)\mathrm{d}t. \quad (4)$$

The second part of (4) can be seen as the total rewards that the source pays for the relay nodes for their help, so (4) is a trade-off between the performance and the cost. Then, this paper gets an optimization problem with the controlling parameters $0 \leqslant u(t) \leqslant 1$.

2.3 Optimal control

The problem in (4) is a continuous time optimization problem, which can be solved by the famous Pontryagin's maximum principle [18]. Before getting the optimal policy, Lemma 1 is first presented, which shows that the optimal solution exists.

Lemma 1 The optimal solution of the optimization problem shown in (4) exists.

Proof This paper will prove this lemma by the Filippov's theorem [19], and it needs to check the following conditions. First, due to $0 \leqslant u(t) \leqslant 1$, the admissible set is close and convex. Second, the right hand side of (2) and (3) is bounded by a linear function about the control and state parameters. In addition, it can easily check that the objective function (4) is convex. Then, the lemma follows. □

Lemma 1 just guarantees a measurable control. To get the optimal policy, it needs the Pontryagin's maximum principle [18]. Based on (2), (3) and (4), the Hamiltonian function H can be got as follows:

$$\begin{gathered} H = \dot{F} - \varepsilon u + \lambda_i \dot{i} + \lambda_F \dot{F} = \\ (1 + \lambda_F)\dot{F} - \varepsilon u + \lambda_i \dot{i} = \\ (1 + \lambda_F)\beta N i(1 - F) - \varepsilon u + \\ \lambda_i \beta N i(1 - i)(1 - (1 - q)(1 - u)). \end{gathered} \quad (5)$$

In (5), the symbols λ_i and λ_F are the co-state/adjoint functions, and their derivations are shown in

$$\begin{cases} \dot{\lambda}_i = -\dfrac{\partial H}{\partial i} = -(1 + \lambda_F)\beta N(1 - F) - \\ \qquad \lambda_i \beta N(1 - 2i)(1 - (1 - q)(1 - u)) \\ \dot{\lambda}_F = -\dfrac{\partial H}{\partial F} = (1 + \lambda_F)\beta N i \end{cases}. \quad (6)$$

In addition, according to [18], this paper gets the transversality conditions as follows:

$$\lambda_i(T) = \lambda_F(T) = 0.$$

Then, from Theorem 3.14 in [18], one can demonstrate that there exist a continuous or piece-wise continuously differentiate state and co-state functions, which satisfy

$$\mu \in \arg \max_{0 \leqslant u^* \leqslant 1} H(\lambda_i, \lambda_F, (i, F), u^*). \quad (8)$$

The symbol u^* denotes the optimal policy. This equation means that the optimization problem in (4) can be changed to maximize the Hamiltonian function. Then, define $f = \partial H / \partial u$, and the optimal policy of u can be obtained as follows:

$$u = \begin{cases} 0, & f < 0 \\ 1, & f > 0 \end{cases}. \quad (9)$$

From (5), we can obtain

$$f = \frac{\partial H}{\partial u} = -\varepsilon + \lambda_i \beta N i(1 - i)(1 - q). \quad (10)$$

Combing (9) with (10), Lemma 3 can be obtained easily. This lemma shows that the optimal policy has a very simple structure. For example, if $h = T$, $u(t) = 1$ in the whole lifetime of the message, it means that the nodes are fully cooperative all the time. Otherwise, the nodes start with a fully cooperative action (before the time h) and then change to the state with fully selfishness. Before introducing this lemma, Lemma 2 is firstly shown, which will be used in the proving process of Lemma 3.

Lemma 2 $1 + \lambda_F > 0$.

Proof Suppose at certain $s < T$, $1 + \lambda_F(s) \leqslant 0$, according to (6),

$$\dot{\lambda}_F - \frac{\partial H}{\partial F} = (1 + \lambda_F)\beta N i \leqslant 0. \quad (11)$$

Therefore, λ_F is non-increasing in $s < t \leqslant T$. This means that $1 + \lambda_F(T) \leqslant 0$, so $\lambda_F(T) \leqslant -1 < 0$, which is contradictory with the transversality condition in (7). Then, the assumption is not rational, and Lemma 2 can be obtained. □

Lemma 3 The optimal policy shown in (9) has a bang-bang structure. That is, there exists a threshold $0 \leqslant h \leqslant T$, where u satisfies $u(t) = 1, t < h; u(t) = 0, t > h$.

Proof First, from (6) and (10), (12) can be got easily.

$$\begin{aligned}\dot{f} = \dot{\lambda}_i\beta i(1-i)(1-q) + \lambda_i\beta\dot{i}(1-2i)(1-q) = \\ -(1+\lambda_F)\beta N(1-F)\beta i(1-i)(1-q) - \\ \lambda_i\beta(1-2i)\dot{i}(1-q) + \lambda_i\beta\dot{i}(1-2i)(1-q) = \\ -(1+\lambda_F)\beta N(1-F)\beta i(1-i)(1-q). \qquad (12)\end{aligned}$$

Since $i(0) = 1/N$, and $0 \leqslant q < 1$, one can get $0 < i(t) \leqslant 1$, $t \leqslant T$. If $i(t) = 1$, all the nodes have got the message, there is no need to consider the incentive policy. Similarly, if $F(t) = 1$, the message has been transmitted to the destination, and the message spreading process will stop. Therefore, it only needs to consider the case $i < 1$ and $F < 1$. Then, according to Lemma 2, one can see that the derivative of f is negative, and f decreases with time. This shows that once $f(s) \leqslant 0$ at time s, one can get $f(t) < 0$, $s < t < T$. Suppose h is the first time, where $f(h) = 0$, and the formula $u(t) = 1$, $t < h$; $u(t) = 0$, $t > h$ can be got. If the time h does not exist, according to the property of the continuous function, it must have $f(T) > 0$ or $f(0) < 0$. In this case, one can set $h = T + \tau$ and $h = 0 - \tau$, respectively. τ is a very small positive value. Based on these analyses, the lemma follows. □

3. Performance analysis

3.1 Simulations

As shown above, the message spreading process is modeled by the mean-field method, which is just an approximation, so it needs to check its accuracy. This paper runs several simulations based on the opportunistic network environment (ONE) simulator [20]. Here, it mainly considers two different mobility models, which are the Poisson contact model and a real motion trace, respectively. The above two models have been used in many works. For the Poisson-contact model, this paper generates 400 nodes, and the contact rate β is set to be 3.71×10^{-6} s^{-1}. The value comes with the Shanghai city motion trace [21]. For the real motion trace, this paper will adopt the famous Infocom'05 motion trace [22]. This dataset collects the trajectories of 41 people. For this trace, this paper first fits it as an exponential model and explores the value of the intermeeting time between two-consecutive contacts. Then, it will use this value to generate 400 nodes. Note that in this section, the main objective is to check the theoretical model's accuracy, so this paper only considers three random incentive policies as an example. In particular, it sets: Case 1, $u(t) = 0$, $0 \leqslant t \leqslant T$; Case 2, $u(t) = 1$, $0 \leqslant t \leqslant T$; Case 3, $u(t) = 0.2$, $0 \leqslant t \leqslant T$. In addition, it sets $q = 0.1$ and $\varepsilon = 1/T$. When T increases from 0 s to 2 000 s, Fig. 1 and Fig. 2 can be got as follows.

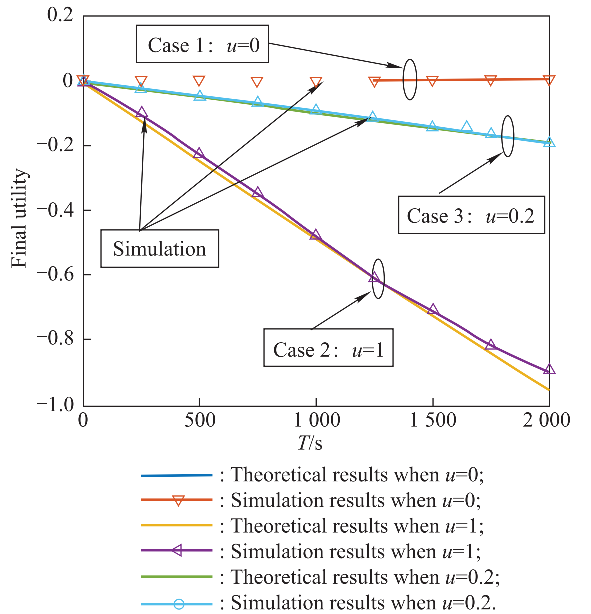

Fig. 1 Final utility comparison between the simulation and theoretical results with Poisson contact model

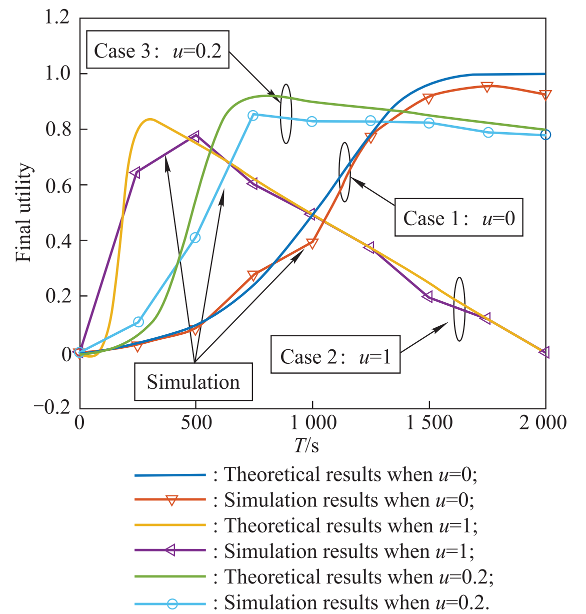

Fig. 2 Final utility comparison between the simulation and theoretical results with Infocom'05 motion trace

In both figures, the marked lines denote the simulation results, and correspondingly other lines denote the numerical results.

From the figures, one can see that the theoretical model is very accurate. For example, the deviation between the simulation and theoretical results in Fig. 1 is smaller than 3.267%, and the deviation in Fig. 2 is about 7.12%. This demonstrates that the mean-field approximation used in this paper is rational. In addition, it can be found that under the same policy, the final utilities may have significant difference. For example, under the policy $u = 1$, the final utility decreases from 0 to -1 in Fig. 1, but it nearly changes within the interval [0,1] in Fig. 2. The main reason for the difference lies in the different settings of the mobility model, where both the inter-meeting time and the number of nodes are different.

3.2 Analysis with theoretical results

The accuracy of the proposed theoretical model has been checked in the former section, so it only considers the numerical/theoretical results here. In particular, it sets β to be 8.41×10^{-5} s^{-1}. As shown above, the performance may be different under the same policy when the settings are different. To further check this phenomenon, this paper sets $T = 1\,000$ s, and let the number of nodes increases from 100 to 1 000. Note that the parameter ε is a constant, which generally increases with the number of nodes. This is intuitive; because if there are more nodes being cooperative, more rewards the source may pay. In this case, when the number of nodes changes, the value of ε should be denoted as $\varepsilon_1 N$. This paper sets $\varepsilon_1 = 500 \cdot (1/T)$, and remains other settings as those in the former section. Considering three different policies with $u = 1$, $u = 0.1$ and $u = 0$, respectively, Fig. 3 is obtained. This result further shows that the final utility changes significantly if the numbers of nodes are different. On the other hand, this result also shows that full cooperation may not be good. For example, the final utility decreases rapidly when $u = 1$. This is because that the rewards the source pays increase progressively with the nodes' number increasing.

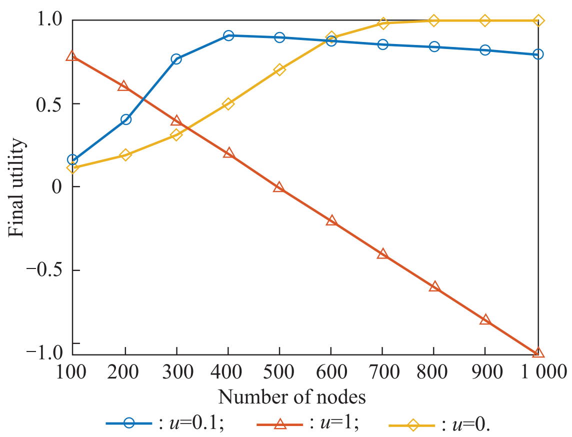

Fig. 3 Utility change with number of nodes

Then, this paper compares the performance of the optimal policy with some other policies'. In particular, it mainly considers five different policies: Case 1, the optimal policy shown in (9); Case 2, $u(t) = 0$, $0 \leqslant t \leqslant T$; Case 3, $u(t) = 1$, $0 \leqslant t \leqslant T$; Case 4, $u(t) = 0.2$, $0 \leqslant t \leqslant T$; Case 5, $u(t) = 0.8$, $0 \leqslant t \leqslant T$. Other settings are the same as those in the former section, and Fig. 4 can be got.

From the result, one can see that the optimal policy obtained is really better than other policies. On the other hand, Fig. 4 shows that the policy with $u = 0$ is better compared with the case with $u = 1$ when $T > 1\,000$ s. In fact, when T is bigger, the message has longer lifetime, so there is enough time for the source to transmit the message to the destination directly. In this case, there is no need to get the help from others, so $u = 0$ is better. In addition, when $T < 100$ s, the lifetime of the message is too short, so even the source gets the help from others, these nodes may not have enough time to transmit the message to the destination. Then, the source may dissipate its rewards, so $u = 0$ is still better than Case 2 with $u = 1$.

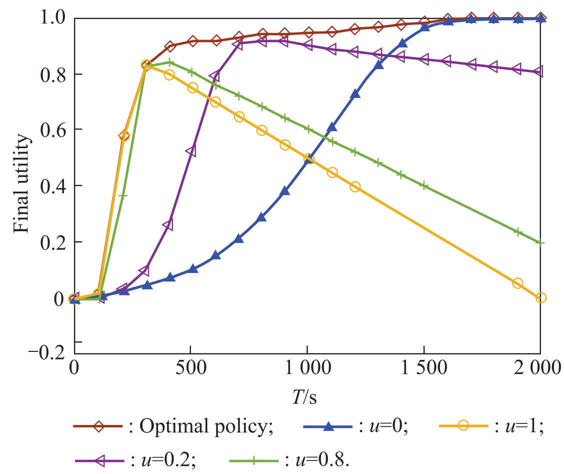

Fig. 4 Comparison with the optimal policy

Note that the optimal policy has a bang-bang structure, that is, there is a threshold, where the value of u will change from 1 to 0. The threshold of the optimal policy in Fig. 4 is shown in Fig. 5.

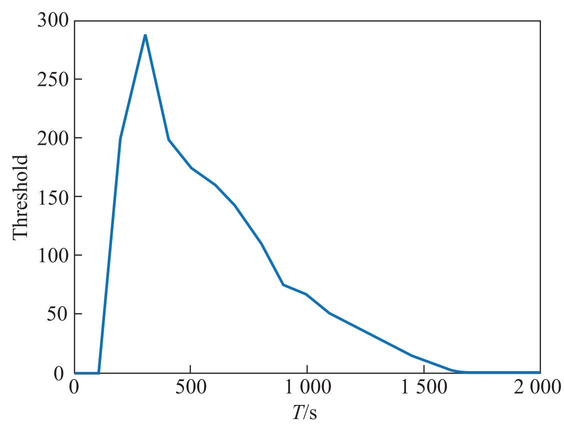

Fig. 5 Threshold of the optimal policy

As an example, the optimal policies when $T = 200$ s, 500 s and 1 500 s are shown in Fig. 6, and all of them conform to the bang-bang structure. When $T = 200$ s, u

equals 1 all the time, and one can see that the threshold appears in the deadline of the message.

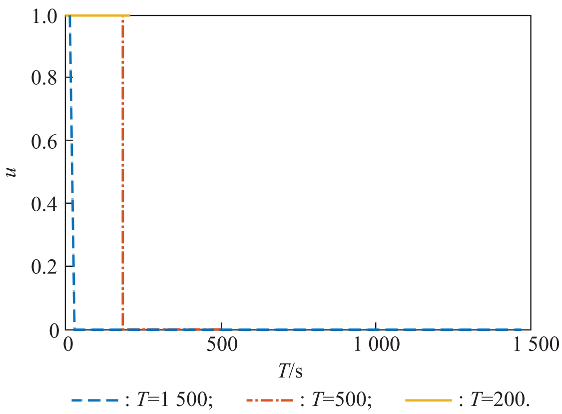

Fig. 6 Optimal policy when T has different values

4. Conclusions

This paper explores the optimal incentive policy to improve the performance of message transmission in the DTN. In particular, it models the incentive problem as an optimization problem with the forwarding probability as the controlling parameter. A mean field model with several ordinary differential equations is used to describe the message spreading process. The model is checked by simulations. Based on the Pontryagin's maximum principle, this paper gets the optimal policy, and mathematically proves that the optimal policy conforms to the bang-bang structure. In future work, we will use this simple policy in some real scenarios, such as the music/document sharing between the students in the university, etc. In addition, the nodes transmitting the messages will cost various resources, such as the bandwidth, power and even the storage, etc. For simplicity, this paper only considers the power as most of the previous works. The case with heterogeneous resources also will be explored in future work.

References

[1] MEHMETIM F, SPYROPOULOS T. Performance analysis of mobile data offloading in heterogeneous networks. IEEE Trans. on Mobile Computing, 2016, 16(2): 482 – 497.

[2] Statista. Global mobile data traffic from 2017 to 2022 (in exabytes per month). https://www.statista.com/statistics/271405/global-mobile-data-traffic-forecast/.

[3] LEE K, LEE J, YI Y, et al. Mobile data offloading: how much can WiFi deliver? IEEE/ACM Trans. on Networking, 2013, 21(2): 536 – 550.

[4] KO H, LEE J, PACK S. Performance optimization of delayed WiFi offloading in heterogeneous networks. IEEE Trans. on Vehicular Technology, 2017, 66(10): 9436 – 9447.

[5] FALL K. A delay-tolerant network architecture for challenged Internets. Proc. of the Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications, 2013: 27 – 34.

[6] LI Q, ZHU S, CAO G. Routing in socially selfish delay tolerant networks. Proc. of the IEEE International Conference on Computer Communications, 2010: 1 – 9.

[7] LU R, LIN X, ZHU H, et al. Pi: a practical incentive protocol for delay tolerant networks. IEEE Trans. on Wireless Communications, 2010, 9(4): 1483 – 1493.

[8] SEREGINA T, BRUN O, ELAZOUZI R, et al. On the design of a reward-base incentive mechanism for delay tolerant networks. IEEE Trans. on Mobile Computing, 2017,16(2): 453 – 465.

[9] CAI Y, FAN Y, WEN D. An incentive-compatible routing protocol for two-hop delay-tolerant networks. IEEE Trans. on Vehicular Technology, 2016, 65(1): 266 – 277.

[10] NGUYEN T, BRUN O, PRABHU B. Mean-field limit of the fixed-reward incentive mechanism in delay tolerant networks. Proc. of the 16th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks, 2018: 1 – 8.

[11] CHEN K, SHEN H, YAN L. Multicent: a multifunctional incentive scheme adaptive to diverse performance objectives for DTN routing. IEEE Trans. on Parallel and Distributed Systems, 2015, 26(6): 1643 – 1653.

[12] JEDAR B, LIU L, QIU T, et al. A game-theoretic incentive scheme for social-arware routing in selfish mobile social networks. Future Generation Computer Systems, 2017, 70(C): 178 – 190.

[13] ZHU H, FU L, XUE G, et al. Recognizing exponential intercontact time in VANETs. Proc. of the IEEE International Conference on Computer Communications, 2010: 1 – 5.

[14] GAO W, LI Q, ZHAO B, et al. Multicasting in delay tolerant networks: a social network perspective. Proc. of the 10th ACM International Symposium on Mobile Ad Hoc Networking and Computing, 2009: 299 – 308.

[15] WU Y, DENG S, HUANG H. Control of message transmission in delay/disruption tolerant network. IEEE Trans. on Computational Social Systems, 2018, 5(1): 132 – 143.

[16] WANG S, KHOUZANI M H R. Optimal control for epidemic routing of two files with different priorities in delay tolerant networks. Proc. of the American Control Conference, 2015: 1387 – 1392.

[17] BARABASI A, ALBERT R, JEONG H. Mean-field theory for scale-free random networks. Physical A: Statistical Mechanics and Its Applications, 1999, 272(1 – 2): 173 – 187.

[18] GRASS D, CAULKINS J, FEICHTINGER G, et al. Optimal control of nonlinear processes: with applications in drugs, corruption, and terror. New York: Springer Verlag, 2008.

[19] GAFF H, SCHAEFER E. Optimal control applied to vaccination and treatment strategies for various epidemiological models. Mathematical Bioscience and Engineering, 2009, 6(3): 469 – 492.

[20] KERANEN A, OTT J, KARKKAINEN T. The ONE simulator for DTN protocol evaluation. Proc. of the 2nd International Conference on Simulation Tools and Techniques, 2009: 55.

[21] Shanghai Jiao Tong University. Shanghai taxi trace. http://wirelesslab.sjtu.edu.cn/download.html.

[22] CRAWDAD Community. Infocom 2005 trace. http://crawdad.cs.dartmouth.edu/meta.ph-p?name=cambridge/haggle.

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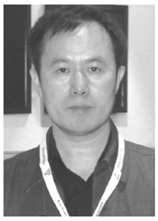

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